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# **An Experimental Test of the No Safety Schools Theorem**

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September 6, 2017

## **CARLETON ECONOMIC PAPERS**



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# An Experimental Test of the No Safety Schools Theorem\*

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## Abstract

In simultaneous search problems individuals choose a portfolio of risky options from a larger menu of options with utility determined by the portfolio's option with the best ex-post outcome. [Chade and Smith \(2006\)](#) examine simultaneous search problems and show that the optimal portfolio includes the utility maximizing option and others that are riskier. However, [Pallais \(2015\)](#) shows that when individuals apply to more colleges, their decisions are inconsistent with theoretical predictions. We replicate this finding experimentally and show that subjects select similar portfolios when the payoffs are independent, suggesting subjects ignore the rival nature of the options.

**Keywords:** Decision Making; Simultaneous Search; Correlation Neglect; Online Experiment; College Application

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# 1 Introduction

Many decisions in life take the form of simultaneous search. The college application decision is a well-known example of this type of problem where a student can apply to many schools but can only enroll in one. In general, these problems involve simultaneously selecting a subset of options from a larger menu. This type of decision problem is unique due to the fact that each option is uncertain, and all the options are rival. In the college application example one can regard each college as having a likelihood of admission, and a specific payoff from enrolling. However, applicants will enroll in their most preferred school to which they are offered admission. Therefore in the college application example there are probabilities of success and payoffs, just like lotteries. However, unlike standard lottery portfolio problems, the payoffs are rival. In this paper, we abstract from the college application example and explore the portfolios of lotteries selected by subjects in this type of environment, using an incentivized online experiment. We demonstrate that the portfolios of lotteries selected by subjects significantly deviate from the optimal portfolio. We then present evidence suggesting that the source of the deviation is due subjects' failure to account for the dependent nature of the lotteries. This can be seen as a form of costly cognition, similar in flavor to correlation neglect. We call this phenomenon "dependence neglect". Our findings help to explain recent findings that show improved college match quality when high schools students are given expert advice.<sup>1</sup>

A theoretical prediction regarding the optimal portfolio in simultaneous search problems is Theorem 2 of [Chade and Smith \(2006\)](#), displayed here for convenience:

**Theorem 2:** The best portfolio  $\Sigma^*$  is more aggressive than the best singletons  $Z_{|\Sigma^*|}$ .

This theorem is referred to as the "no safety schools" theorem hereafter. [Chade and Smith \(2006\)](#) shows that when an individual picks one lottery (e.g., sends one application) she picks the lottery that maximizes her expected utility. With certain assumptions regarding the payoffs and probabilities, if instead an individual picks several lotteries, her portfolio of lotteries (e.g., portfolio of applications) will include the expected utility maximizing lottery along with other lotteries that are riskier than her expected utility maximizing lottery. In the college application example, this

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<sup>1</sup>See for instances, [Carrell and Sacerdote \(2013\)](#); [Hoxby and Avery \(2013\)](#); [Carrell and Sacerdote \(2017\)](#).

means that if an individual applies to two colleges, one of the colleges she applies to will be weakly riskier than the college she would apply to if she were only to apply to one college.

However, recent empirical work suggests that individuals do not make decisions consistent with the no safety schools theorem. In a study of an exogenous increase in the default number of score reports that a student can send to schools after taking the ACT college aptitude test, [Pallais \(2015\)](#) finds that students on average sent score reports to both riskier risky colleges *and* safer safe colleges. This result is inconsistent with the no safety schools theorem, which would predict that students apply only to riskier (i.e., more selective) schools that offer a higher ex-post payoff. While [Pallais \(2015\)](#) demonstrates that prospective students make decisions that are inconsistent with the no safety schools theorem, it is difficult to identify why prospective students fail to select optimal portfolios. For instance, prior to sending out applications, students receive advice from parents, friends, and others within their social circle who may influence their decisions (c.f., [Galotti and Mark, 1994](#); [Roderick et al., 2011](#)). Additionally, while researchers can readily acquire an estimate of the benefit from attending a particular school (e.g., income after graduation), these estimates will not include idiosyncratic benefits known only to the decision maker (e.g., the value of attending the same school as a romantic partner). Thus, it is difficult to identify if students are failing to make application decisions consistent with the no safety school theorem because of the complexity of the problem, or because personal reasons rationalize the observed choices (e.g., there is not a common value for each school).

We design and implement an online experiment to test whether individuals make decisions consistent with the no safety schools theorem. We have two primary treatments, RIVAL and RANDOM. In RIVAL, subjects choose a portfolio of  $k$  lotteries from a fixed menu of lotteries. All the lotteries are then played and subjects earn the highest (successful) prize from the outcomes of the lotteries in their portfolios. In RANDOM treatments, subjects also choose a portfolio of  $k$  lotteries from the same fixed menu of lotteries. In RANDOM, subjects are paid based off of the outcome of one randomly selected lottery in their portfolio.

We shape our experimental design to match the fixed sample size case discussed in [Chade and Smith \(2006\)](#) in which the number of lotteries a subject can select is exogenously assigned. When applying to college, the vast majority of students

(roughly 75-80 percent) send the default number of score reports (Pallais, 2015) - which is analogous to having the number lotteries assigned rather than endogenously determined.<sup>2</sup> However, it is important to note that this design choice does not impact the primary predictions of the no safety schools theorem. This is because one can think of our design as a special case in which the cost of the first  $k$  lotteries is zero and the cost of the  $k + 1$  lottery is infinity.<sup>3</sup>

Using a between subjects design, we first compare the portfolios of lotteries chosen by subjects who are allowed to select many lotteries to the portfolios of lotteries chosen by subjects who are allowed to pick fewer lotteries, when payoffs are rival. Consistent with Pallais (2015), in the RIVAL treatment, we find that subjects who choose more lotteries choose riskier risky and safer safe lotteries. This is inconsistent with the no safety schools theorem which predicts that subjects would only choose riskier risky lotteries.

We then compare choices made under the RANDOM treatment to choices made under the RIVAL treatment as a further test of the no safety schools theorem. In RANDOM, we use the same menu of lotteries and portfolio sizes but pay subjects based on the outcome of one of the lotteries in their portfolio which a computer selects at random. In this treatment the outcomes are uncertain but they are not rival. Accordingly, the no safety school theorem does not apply. Utility maximization in this treatment predicts that subjects will choose the expected utility maximizing lottery, and safer safe and riskier risky lotteries as the portfolio size increases. Thus, if subjects are maximizing expected utility then larger portfolios should lead to safer safe lotteries in RANDOM but not in RIVAL.

Holding constant the number of lotteries the subject is allowed to choose, we find that subjects behave nearly identically in RANDOM and RIVAL treatments. The behavior we observe can be thought of as a flavor of correlation neglect. Only here, subjects seem to ignore the dependence of the lotteries rather than the correlation. Past studies document the failure of individuals to account for the correlation of financial assets in portfolio allocation decisions (Eyster and Weizscker, 2011; Kallir

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<sup>2</sup>While of course the number of schools a student applies to is endogenous for some students, we think it is reasonable to regard a typical student as treating the number of applications as exogenous.

<sup>3</sup>Another departure from the college application problem worth mentioning is that our design implies that college enrollment probabilities are uncorrelated - which is generally not the case. Fortunately, the no safety schools theorem is robust to correlated outcomes, where the probability of getting into a school above a certain threshold is reduced by a common scalar (see section 3C of Chade and Smith (2006) for a discussion).

and Sonsino, 2009) and informative signals received within a network (Chandrasekhar, Larreguy, and Xandri, 2015). In these experiments, subjects treat the assets, or signals, as though they were independent. Similarly, we find that subjects make nearly equivalent decisions regardless of whether the outcomes are independent or dependent. This is similar to correlation neglect as subjects are ignoring the fact that the payoff depends on the outcomes of all the lotteries in their portfolio when the lotteries are rival. We refer to this as “dependence neglect”, where subjects appear to treat dependent outcomes as independent and explore this as a possible explanation in Section 6.

## 2 Theory

To illustrate the implications of the no safety schools theorem in the RIVAL treatment consider the expected value of a portfolio containing two lottery selections. Imagine an individual chooses two lotteries, A and B, where lottery  $i$  wins prize  $\omega_i$  with probability  $\rho_i$  and wins 0 with probability  $1 - \rho_i$ , where  $i \in \{A, B\}$ . In the RANDOM treatment the expected value is:

$$\frac{1}{2}(\rho_A \times \omega_A + (1 - \rho_A) \times 0 + \rho_B \times \omega_B + (1 - \rho_B) \times 0). \quad (1)$$

Thus, in the RANDOM treatment, the probability of lottery A being used to determine the individual’s payoffs depends on the number of choices being made, but not on the magnitude of the payoffs between the lotteries in the portfolio. The expected value is thus an equally weighted average of the expected value of the lotteries in the portfolio. The compound lottery from such a portfolio is:

$$\text{payout} = \begin{cases} \omega_A & \text{w.p. } \rho_A \times 1/2 \\ 0 & \text{w.p. } (1 - \rho_A) \times 1/2 \\ \omega_B & \text{w.p. } \rho_B \times 1/2 \\ 0 & \text{w.p. } (1 - \rho_B) \times 1/2 \end{cases}$$

However, in the RIVAL treatment the subject only receives the ex-post most favorable

outcome, thus the expected value is:

$$\begin{cases} \rho_A * \omega_A + (1 - \rho_A)\rho_B\omega_B + (1 - \rho_A)(1 - \rho_B)0 & \text{if } \omega_A > \omega_B \\ \rho_B * \omega_B + (1 - \rho_B)\rho_A\omega_A + (1 - \rho_B)(1 - \rho_A)0 & \text{if } \omega_B > \omega_A. \end{cases}$$

Consequently, the expected value depends not only on the number of choices, but also on the payouts of the other lotteries. The compound lottery from such a portfolio is:

$$\text{payout} = \begin{cases} \text{if } \omega_A > \omega_B \begin{cases} \omega_A & \text{w.p. } \rho_A \\ \omega_B & \text{w.p. } \rho_B(1 - \rho_A) \\ 0 & \text{w.p. } (1 - \rho_B)(1 - \rho_A) \end{cases} \\ \text{if } \omega_B > \omega_A \begin{cases} \omega_B & \text{w.p. } \rho_B \\ \omega_A & \text{w.p. } \rho_A(1 - \rho_B) \\ 0 & \text{w.p. } (1 - \rho_A)(1 - \rho_B) \end{cases} \end{cases}$$

As a result the compound lottery depends not only on the outcomes of the other lottery, but also which lottery has a higher prize. Obviously, as the size of the portfolio increases so does the complexity of the expected value of the portfolio. Thus, it may be the case that subjects' find calculating the optimizing bundles to be cognitively costly.<sup>4</sup> One response to the cognitive cost of calculating the optimal bundle would be to ignore the dependence between the lotteries. If subjects do so, then the 'perceived' or 'computed' payouts in the RIVAL and RANDOM treatment are identical.

[Chade and Smith \(2006\)](#) (C&S, hereafter) study the properties of the optimal portfolio when payoffs are rival. C&S show that the best portfolio contains the choice with the highest expected utility. With  $k > 1$ , the decision maker does not select safer choices (i.e., higher probability of success) unless the safer choice offers a higher expected utility (e.g., higher prize). Consequently, C&S state that "static portfolio maximization precludes 'safety schools'." In the context of our experiment this implies two things: (i) the best portfolio will include the lottery offering the highest expected utility and (ii) that the lotteries chosen when  $k \geq 2$  will be made up of lotteries that are weakly riskier than the lottery selected when  $k = 1$ , where  $k$  is the number of

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<sup>4</sup>That is one might need to exert some effort in order to perform such calculations, as in [Tirole \(2009\)](#).

lotteries the subject is allowed to select. For narrative purposes, we will refer to this form of decision making as EU, for expected utility maximization.<sup>5</sup> In Section 4 we analyze the implications of the no safety schools theorem for the choices involved in our experiments.

### 3 Methods

We conduct experiments on Amazon Mechanical Turk (AMT). The experiment is programmed in JavaScript and HTML. AMT is an online workplace where workers (or subjects, in the context of an experiment) complete Human Intelligence Tasks (HITs) posted by requesters (the experimenters) for pay. HITs are typically posted in batches of 25 to 100. Batches may be thought of as equivalent to sessions in the lab where the number of HITs in a batch is the number of subjects that can participate in a given session. HITs are usually short and take about 5 to 10 minutes to complete and typically pay under a dollar. The hourly wage for workers on AMT is generally quite low. A recent Pew Poll finds that a little over 50% of workers report earning less than 5 dollars per hour. Our hourly wage is significantly higher than the typical hourly wage earned by AMT workers and comes out to around \$9.50 per hour.<sup>6</sup> Payments to subjects are made through Amazon Payment accounts that are linked to workers' randomly generated AMT worker ID numbers. Payments are made in US dollars. Subjects' compensation for completing an HIT typically has two components: 1) a fixed participation fee (analogous to a show-up fee in laboratory studies) and 2) a bonus awarded at the discretion of the experimenter after the subject has completed and submitted the HIT. The fixed participation fee is the same for all subjects while the bonus can be any amount. If a subject does an especially poor job (e.g., does not complete the HIT), the requester has the option of rejecting the HIT. This is costly to subjects because rejected HITs negatively impact the subject's approval percentage (i.e., approved HITs divided by the number of HITs completed). Once a subject's approval percentage gets too low, they are no longer eligible for many of the HITs

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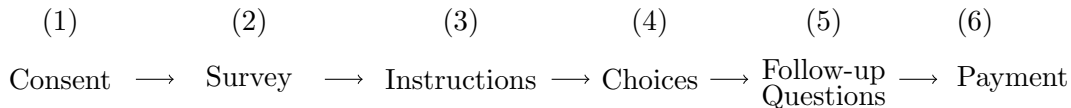
<sup>5</sup>One may think of EU as a fully rational benchmark, e.g., the individual has the ability to make EU calculations, does not make math errors, understands the nature of the payoffs, with no cognitive costs.

<sup>6</sup>Paul Hitlin "Research in the Crowdsourcing Age, a Case Study" <http://www.pewinternet.org> July 7, 2016. July 24, 2017



posted on AMT.<sup>7</sup>

Figure 1: Experimental Timeline



The experiment’s procedures follow 6 stages presented as a timeline in Figure 1. At no point can subjects go back and change their responses. In the first stage, subjects accept the HIT and consent to participate in the experiment and have their data used in academic research. After accepting the HIT subjects move to the second stage where they complete a short survey, which collects basic demographics, tests the subject’s ability to calculate expected value, and ensures that the subject understands written English. Subjects who incorrectly answer the English comprehension question are not allowed to continue and are instructed to return the HIT so another subject can complete it.<sup>8</sup> After the survey is completed, subjects move to the third stage (3 in Figure 1) where they are given instructions that vary by treatment.

After viewing experimental instructions, subjects start the fourth stage where they make their actual lottery choices. In the fourth stage of the experiment, subjects are asked to select  $k$  lotteries (where  $k$  is 1,2,4, or 6) from a set of 20 lotteries. These lotteries are shown in Table 1 and are fixed for all subjects. The lotteries range from a 5% chance to win 5\$ to a 100% chance to win \$0.25. The experiment is a between subjects design. Subjects participate once and only see one payment rule and select either 1,2,4, or 6 lotteries from the set of 20. Subjects observe each lottery’s prize and the probability of winning. To prevent confusion, we present each lottery’s expected value.<sup>9</sup> We vary the number of choices to explore how choices differ across subjects

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<sup>7</sup>While there are some concerns that workers are not paying attention to the instructions and instead breeze through HITs as fast as possible in order to maximize their days’ earnings, [Hauser and Schwarz \(2016\)](#) shows the opposite. Workers on AMT tend to be just as, if not more, attentive to instructions than laboratory subjects. Given that poor work is punished severely, in the form of rejected HITs, this is unsurprising. Thus in some ways AMT offers an ideal environment to run complicated decision experiments. Additionally, [Mullinix, Leeper, Druckman, and Freese \(2015\)](#) shows that AMT results are quite comparable to student-based samples.

<sup>8</sup>Ideally, we would have preferred to conduct the survey after the main experiment however the requirement that subjects be able to comprehend English required us to begin with the survey.

<sup>9</sup>As a robustness check, we later remove expected values and have a different set of subjects participate in a session with 4 choices. There are no significant differences in choices. These results are available upon request.

who are given relatively few choices from those who are given more choices. We also vary the payment rule. Payments are either RIVAL and based on the maximum successful outcome of the subject’s lottery choices, or RANDOM and based on one randomly selected lottery. We use these two payment rules to explore whether or not subjects’ choices differ across the payment rules, holding the number of choices fixed. We only observe whether or not a subject selected a given lottery. We chose this between subjects design for two reasons: i) when students initially select what schools to send their ACT/SAT score reports to they do so simultaneously and ii), we wanted to avoid as much confusion as possible. While having subjects pick their lotteries sequentially might have some advantages (i.e., observe their first, second,..., and  $k^{th}$  lottery selected), this might cause subjects think that it was a sequential search problem whereas having  $k$  fixed avoids that possibility.

We refer to treatments using both payment rule (RANDOM or RIVAL) and the number of choices (1, 2, 4, and 6). Therefore, we have seven treatments. This is because 1|RIVAL and 1|RANDOM have identical payment rules. We refer to the treatment in which subjects are given a single choice as “1”. This treatment serves as our control. To simplify the analysis, we index the lotteries from 1 to 20. Lotteries lower in number are riskier but have a higher payout.<sup>10</sup> In the experiment, however, lotteries are labeled by letter. In the fifth stage subjects answer two follow-up

Table 1: Lotteries Used in Experiment

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
Prob	.05	.10	.15	.20	.25	.30	.35	.40	.45	.50	.55	.60	.65	.70	.75	.80	.85	.90	.95	1.00
Prize	5.00	4.75	4.50	4.25	4.00	3.75	3.50	3.25	3.00	2.75	2.50	2.25	2.00	1.75	1.50	1.25	1.00	0.75	0.50	0.25
EV	0.25	0.48	0.68	0.85	1.00	1.13	1.23	1.30	1.35	1.38	1.38	1.35	1.30	1.23	1.13	1.00	0.85	0.68	0.48	0.25

questions that relate to their choices in the previous stage and complete a second short survey. The follow-up questions relating to subjects’ choices ask subjects to indicate what they consider to be the best/favorite and worst/least favorite lotteries from the 20 possible lotteries. While answering these questions, subjects see which lotteries they selected but are unconstrained by their prior selections. Subjects do not know the outcome of the lotteries they selected (their payoffs) when identifying

<sup>10</sup>We use this set of lotteries to mirror an environment where there is an inverse relationship between the value of the prize and the likelihood of winning the prize. For example, when selecting what college to apply to, students, of all quality types, may apply to schools which they are less likely to be admitted into and schools which they are more likely to be admitted into. Presumably, the schools with higher labor market returns are more selective.

the best and worst lottery.<sup>11</sup> The other demographic questions in the final survey include a subjective risk preference question, the Barratt Impulsiveness Scale questions (Barratt et al., 1975) and others. The risk question comes from the German Socio-Economic Panel Survey. The question’s English translation is worded as follows:

*How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?*

Subjects answer this question on an 11 point scale ranging from 0 to 10 - with 0 corresponding to “I avoid risk” and 10 corresponding to “Fully prepared to take risks.” We use this question because Dohmen et al. (2011) shows that subjects indicating a greater willingness to take risks are also more willing to take risks in a conventional lottery experiment. Similar results are observed in Nosić and Weber (2010) and Lönnqvist et al. (2015). Naturally, the portfolio of lotteries subjects select depends on their exogenous and idiosyncratic risk preferences. We use the answers to the question above to control for this heterogeneity when estimating treatment differences and to test for possible selection into the experiment. Once the final survey is completed, subjects are instructed to submit the HIT. In the sixth and final stage, subjects are informed (by email) of the results of their lottery choices and are paid based on the outcome of those choices. Subjects are paid a 25 cent participation fee, plus their bonus. Subjects can only participate once, verified by the unique AMT worker ID number. The survey questions along with the experimental instructions can be found in Appendix E. A screenshot of an example choice page can be found in Appendix F.

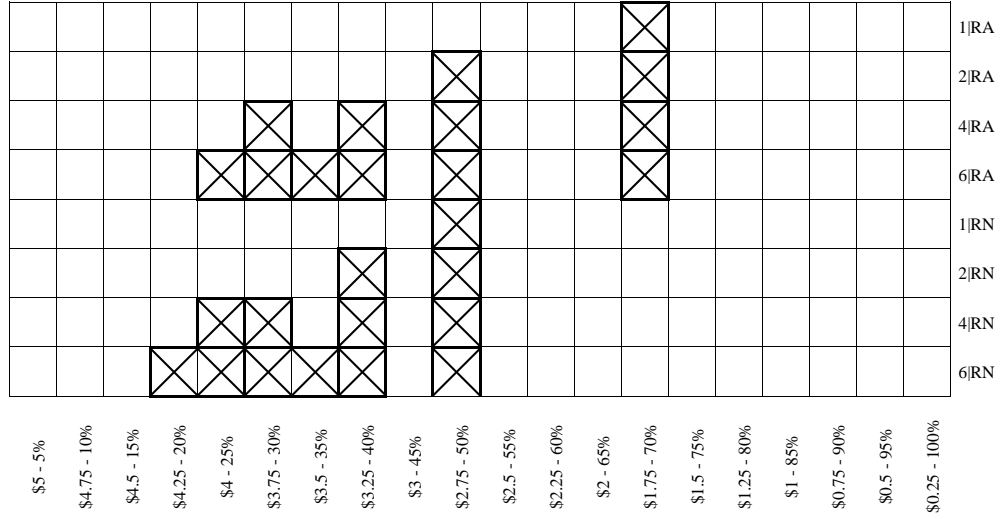
## 4 Hypotheses

Given the lotteries used in our experiment, we calculate the portfolio of lotteries which maximize the expected utility for  $k = 1, 2, 4$ , and 6 for a risk averse (RA) and risk neutral (RN) agent. The risk averse agent has exponential utility (i.e.,  $u(\omega) = \omega^\alpha$ ) with  $\alpha = .5$ . The results of these calculations are shown in Figure 2, where RA indicates the optimal portfolio for the risk averse agent and RN indicates the optimal portfolio for the agent who is risk neutral. “X” indicates that a lottery is an element of an optimal portfolio.

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<sup>11</sup>However, subjects are given this information when they are paid their bonus about a day later.

Figure 2: Optimal Choices by Portfolio Size and Risk Aversion



**Notes:** Elements of the EU maximizing bundles. RA indicates risk aversion and RN indicates risk neutrality.

As predicted under the no safety school theorem in C&S all optimal portfolios include the expected utility maximizing lottery. Additionally, as  $k$  increases the optimal portfolio includes only lotteries that are riskier than the  $k = 1$  choice.

We posit two primary hypotheses derived from the no safety schools theorem which we test using the experiment discussed above. These hypotheses are stated below in terms of the null hypothesis that subjects are expected utility maximizers.

**Hypothesis 1** *In RIVAL treatments, the safest lottery selected by subjects is invariant to  $k$ .*

Given that subjects in most treatments select more than one lottery, if we fail to reject Hypothesis 1, then subjects in RIVAL should choose increasingly risky lotteries as  $k$  increases. Because lotteries that are riskier have a lower index number, the average index number of the lotteries selected should also decrease in  $k$ .

**Hypothesis 2** *Holding  $k$  fixed, the pattern of choices will be significantly different across RANDOM and RIVAL. More specifically, relative to RANDOM, bundles in RIVAL will have riskier risky lotteries and riskier safe lotteries.*

Recall that if subjects' payoffs are determined by a lottery selected at random then an expected utility maximizer would select the  $k$  lotteries with the highest expected

utility. Thus, the RANDOM payoff rule should lead to a different pattern of choices than what is depicted in Figure 2.

## 5 Results

Across all treatments, 294 subjects participate in the experiment. Subjects earn between \$0 and \$5 (US), in addition to the 25 cent participation fee. On average subjects spend about 16 minutes completing the experiment and earn \$2.33 - translating to a hourly wage of about \$ 9.60 per hour or about double the typical hourly wage earned by an AMT worker. The number of subjects (N) in each treatment is presented in Table 2 along with the average expected value of the bundles selected by subjects (EV) and the expected value of the bundle that maximizes expected earnings (MEE). Each subject’s chosen lottery portfolio can be found in Appendix D (Figures D.1 and D.2). To give an idea of how much money is being left on the table, we present the difference between the average expected value of the bundles selected by subjects and the expected value of the bundle that maximizes expected earnings % DIFF. On average, in RIVAL, subjects leave about 20 % of the potential earnings or about \$0.50.<sup>12</sup>

Table 2: Treatments, Average Earnings, and Expected Value of Optimal Bundle

		1	2	4	6	TOTAL
RIVAL	N	47	44	43	43	177
	EV	1.14	1.80	2.27	2.59	
	MEE	1.375	2.125	2.959	3.420	
	%DIFF	0.171	0.153	0.232	0.243	
RANDOM	N	-	39	38	40	117
	EV	-	1.13	1.12	1.09	
	MEE	-	1.375	1.363	1.342	
	%DIFF	-	0.178	0.1783	0.188	
TOTAL		47	83	81	83	294

Table 3 presents summary statistics of demographic characteristics and choices.

<sup>12</sup>While this may seem like a small amount, it is slightly more than what a subject could expect to earn if they completed a different task on AMT.

Variable descriptions are found in Appendix A.<sup>13</sup> Roughly 90% of subjects are American and almost all of the remaining subjects are Indian. The data is generally complete as the software prevents empty fields.<sup>14</sup> As shown in the Appendix (Table B.1), reported demographics and individual characteristics are approximately equal across treatments.<sup>15</sup>

Table 3: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
AGE	294	34.771	19.06	18	323
MALE	294	0.631	0.483	0	1
INCOME	293	4.275	2.813	1	10
EDUC	294	4.756	1.728	1	7
RISK	293	5.179	2.78	0	10
AMB	294	0.473	0.5	0	1
FAVORITE	294	11.372	4.713	1	20
LEAST FAV.	294	7.318	8.514	1	20
RISKIEST	294	8.411	4.599	1	20
SAFEST	294	13.661	4.233	1	20
AVERAGE	294	11.22	3.668	1	20
PICKED FAV.	294	0.723	0.448	0	1

We first present two results demonstrating that subjects do not adhere to the no safety schools theorem. We then provide evidence suggesting subjects are mostly treating the lotteries as if they are independent, but not perfectly so.

**Result 1** *The safest lottery selected is increasing in the number of lotteries in the portfolio,  $k$ .*

Table 4 presents the results of models testing the no safety school theorem, a test of Hypothesis 1. Models 1 and 2 are Tobit estimates of the safest lottery subject  $i$

<sup>13</sup>We gather information regarding the gender, age, education, country of residence, and income of subjects. We use these variables to control for individual characteristics when testing the no safety school theorem.

<sup>14</sup>There is some user error, as can be seen in Table 3, one subject reported to be over 300 years old and one subject was able to bypass the income question in the first session. As we are unable to identify all of the errors in reported information, we include this observation. Results without outliers are available upon request.

<sup>15</sup>However, 4|RIVAL has more male subjects; 6|RIVAL has more educated subjects; 6|RANDOM has a higher percentage of ambiguity averse subjects; 1 has older subjects (due to the subject who mistakenly entered their age as 323 years old); 2|RIVAL has subjects that are more prepared to take risks. These are the only statistically significant differences to report.

chose as a function of their assigned treatment relative to the control (1). Models 3 and 4 are OLS estimates of the average index number of the lotteries subject  $i$  chose as function of their assigned treatment relative to the control. All models use robust standard errors. Odd numbered models in Table 4 are baseline models with no control variables. Even numbered models demonstrate that the results are robust to the inclusion of demographics and risk preferences. Positive coefficients correspond to safer choices relative to the control and negative coefficients correspond to riskier choices, again, relative to the control. Models 1 and 2 demonstrate that subjects in 2|RIVAL, 4|RIVAL and 6|RIVAL select a safest lottery that is statistically significantly safer than the safest lottery selected by subjects in the control. This is inconsistent with the no safety school theorem and evidence against Hypothesis 1.

We now explore differences across treatments. For each model in Table 4 we test the equality of coefficients. The null hypothesis of these tests is that the safest lottery selected in a given treatment is equal to the safest lottery selected in a different treatment (e.g.,  $H_0: 2|RIVAL = 6|RIVAL$ ). We reject the null in the case of 2|RIVAL vs 4|RIVAL and 2|RIVAL vs 6|RIVAL. The estimated difference in the safest lottery selected in 4|RIVAL and 6|RIVAL is not statistically significantly different.<sup>16</sup>

We now discuss Models 3 and 4 in Table 4 which test an implication of Hypothesis 1. Recall that the no safety school theorem implies that as the number of choices increases, the decision maker will select increasingly risky choices. In the context of the experiment, this means that as the number of lottery choices ( $k$ ) increases, the average lottery index number should fall (i.e., the average index number of the lotteries in a given bundle). Models 3 and 4 demonstrate that subjects who are given more choices have an average lottery index number that is *not* significantly different than subjects in the control (1). Additionally, none of the F-tests of equality of coefficients reject the null hypothesis that the average lottery index number is equal across treatments.

**Result 2** *Holding  $k$  fixed, subjects choose portfolios that are broadly equivalent in RIVAL and RANDOM treatments.*

Having seen that the selected portfolios have the same average lottery index number across  $k$  we now test whether portfolios change when the outcomes are not rival.

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<sup>16</sup>However, this is not surprising considering that the proportional increase in the number choices is smaller moving from 4 to 6. Still it is important to note that the direction of the coefficient estimate is in the direction opposite of theoretical predictions under EU.

Table 4: Testing the No-Safety School Theorem

Dependent Variable	SAFEST		AVERAGE	
	Model 1	Model 2	Model 3	Model 4
2 RIVAL	2.139** (0.895)	1.703* (0.931)	0.302 (0.78)	0.29 (0.863)
4 RIVAL	4.339*** (0.979)	4.385*** (0.907)	0.465 (0.863)	0.705 (0.826)
6 RIVAL	5.706*** (0.979)	5.709*** (0.944)	1.068 (0.819)	1.325* (0.79)
CONSTANT	10.875*** (0.683)	10.769*** (1.571)	10.936*** (0.637)	11.945*** (1.423)
CONTROLS	-	✓	-	✓
$R^2$	0.0411	0.0563	0.0113	0.119
H <sub>0</sub> : 2 RIVAL = 4 RIVAL	0.0155	0.005	0.8253	0.6076
H <sub>0</sub> : 2 RIVAL = 6 RIVAL	0.0001	0.0001	0.2641	0.1658
H <sub>0</sub> : 4 RIVAL = 6 RIVAL	0.1607	0.1648	0.439	0.4049

**Notes:** Robust standard errors in parentheses. \*\*\*:  $p < .01$ , \*\*:  $p < .05$ , and \*:  $p < .10$ . Models 1 and 2 are Tobits - censored at 1 ( $n = 3$ ) and 20 ( $n = 21$ ) - estimating the safest safe lottery a subject chose. Models 3 and 4 are OLS and estimate the average lottery.  $n = 177$ . Controls in Models 2 and 4: age, subjective risk preferences, education, income, and gender. Coefficient estimates of the controls are available upon request. Probability values derived from F-tests of equality of coefficients presented in the final 3 rows.



To do so, we estimate a similar set of models to those in Table 4 but now include data, and dummy variables, corresponding to the treatments in which subjects' payoffs are determined by the outcome of a randomly selected lottery (RANDOM). If subjects are not taking into account the rival nature of the lotteries then, holding the number of choices fixed, lottery choices should be the same across RANDOM and RIVAL treatments. These results are presented in Table 5. Models 5 and 6 are Tobit estimates of the safest lottery a subject selected as a function of their assigned treatment (i.e., number of choices and payment rule). Models 7 and 8 are OLS estimates of the average index number of the lotteries selected as a function of the assigned treatment. The omitted treatment in all models is the control (1). As a robustness check, Models 6 and 8 include the same demographic controls included in Models 2 and 4 in Table 4. As in Table 4, positive(negative) coefficient estimates correspond to safer(riskier) lotteries relative to the control.

We reject the null of Hypothesis 2 and find evidence that subjects choose broadly equivalent portfolios in the RIVAL and RANDOM treatments. All of the coefficients in Model 5 and Model 6 are positive, suggesting subjects given more choices in both RIVAL and RANDOM treatments select safer lotteries relative to those given only one choice. Moreover, the majority of these coefficients are highly statistically significant and the coefficients tend to increase with  $k$ . We now compare the pattern of lottery selections in RANDOM and RIVAL, holding  $k$  fixed. Below each model in Table 5 we test, using a series of F-tests, the null hypotheses that subjects in RANDOM treatments select a safest/average lottery that is the same as subjects in RIVAL treatments, holding the number of choices constant (e.g.,  $H_0: 2|RIVAL = 2|RANDOM$ ). In the majority of cases, we fail to reject the null hypothesis. Given that the pattern of behavior in RIVAL is similar to what is observed in RANDOM, this suggests subjects are making decisions as if the lotteries are independent. While we reject the null when subjects are given 6 choices, this rejection works against the no safety school theorem because subjects in 6|RIVAL have a safer safe lottery and select lotteries that are on average safer than those in 6|RANDOM.

## 6 A Possible Explanation

As an explanation for the observed behavior, we consider a naive (or costly cognition) decision rule - partly motivated by the findings observed in [Pallais \(2015\)](#) - that

Table 5: Do Subjects Understand the Joint Probabilities? No.

Dependent Variable	SAFEST		AVERAGE	
	Model 5	Model 6	Model 7	Model 8
2 RIVAL	2.139** (0.892)	2.278** (0.929)	0.302 (0.78)	0.624 (0.834)
2 RANDOM	1.426 (0.936)	1.511 (0.985)	-0.321 (0.881)	-0.127 (0.936)
4 RIVAL	4.339*** (0.975)	4.714*** (0.936)	0.465 (0.864)	0.806 (0.84)
4 RANDOM	3.634*** (1.023)	3.573*** (0.987)	0.939 (0.888)	0.883 (0.843)
6 RIVAL	5.707*** (0.971)	5.937*** (0.965)	1.068 (0.82)	1.425* (0.82)
6 RANDOM	3.917*** (0.988)	3.819*** (0.988)	-0.445 (0.822)	-0.498 (0.853)
CONSTANT	10.875*** (0.681)	4.412*** (1.304)	10.936*** (0.638)	5.529*** (1.119)
CONTROLS	-	✓	-	✓
$R^2$	0.0302	0.0405	0.0212	0.1139
H <sub>0</sub> : 2 RAND = 2 RIVAL	0.4077	0.4212	0.4107	0.3743
H <sub>0</sub> : 4 RAND = 4 RIVAL	0.4908	0.2302	0.5776	0.9201
H <sub>0</sub> : 6 RAND = 6 RIVAL	0.0683	0.0376	0.0394	0.0137

**Notes:** Robust standard errors in parentheses. \*\*\*:  $p < .01$ , \*\*:  $p < .05$ , and \*:  $p < .10$ . Models 5 and 6 are Tobits - censored at 1 ( $n = 3$ ) and 20 ( $n = 36$ ) - estimating the safest safe lottery a subject chose. Models 7 and 8 are OLS and estimate the average lottery.  $n = 294$ . Controls that are included in Models 6 and 8 are age, subjective risk preferences, education, income, and gender. Coefficient estimates of the controls are available upon request. Probability values derived from F-tests of equality of coefficients presented in the final 3 rows.

subjects may use. Under this rule subjects treat the outcomes as if they are independent and thus ignore joint probabilities. In this case, the decision maker is selecting choices as if the lotteries were independent and equally likely to be relevant for the payout. One can regard this as ‘dependence neglect’ as the expected value that is being maximized is the same as Equation (1). This is a ‘kissing cousin’ to correlation neglect, in that individuals ignore the dependence of the individual components when calculating the expected value of the portfolio. EU maximization results in subjects selecting riskier lotteries when  $k$  increases, hence the ‘no safety schools’ terminology. However, under dependence neglect, subjects ignore the rival nature of payoffs, resulting in subjects selecting the  $k$  items with the highest independent expected utility. Thus, the lotteries in the portfolio, when  $k > 2$ , are riskier and safer than the choices made when  $k = 1$ .

**Conjecture 1** *Rather than treating outcomes as rival, subjects exhibit dependence neglect, treating the outcomes as independent.*

The results in Section 5 suggest that subjects are treating the lotteries as if they are independent rather than rival. In particular, Result 2 suggests that subjects are evenly splitting their choices between riskier risky and safer safe lotteries which is consistent with dependence neglect. However, as we will show, there is some deviation from this behavior.

If subjects are treating outcomes as independent in the RIVAL treatments, we would expect subjects to select a series of adjacent lotteries (e.g., 8, 9, 10, and 11). We would also expect that these lotteries would be evenly centered around their utility maximizing lottery - meaning subjects are selecting the  $k$  lotteries with the highest expected values. In figures not shown but analogous to Figure 2, the dependence neglecting portfolio always includes the  $k = 1$  choice in addition to lotteries that are riskier and safer than this choice. While we did not ask each subject for their  $k = 1$  choice, we did ask them to identify their favorite lottery. We will use this as a proxy for their utility maximizing lottery. In the control (1), 63% of subjects selected their favorite lottery, and over 80% of subjects select either their favorite lottery or an adjacent lottery in this treatment. An analysis of the determinants of favorite and least favorite lotteries is found in Appendix C. As expected, a subjects’ favorite lottery is increasing (i.e., safer) in their stated risk aversion. This suggests the stated favorite lottery is highly correlated with the utility maximizing lottery. Thus,

dependence neglect implies that the safest(riskiest) lottery would be on average  $\frac{k-1}{2}$  lotteries greater(less) than their favorite lottery.

**Result 3** *Subjects' lottery selections are largely consistent with Conjecture 1. However, the safest lotteries selected are safer than what would be predicted under Conjecture 1*

Approximately 50% of subjects in RIVAL treatments, across all values of  $k \geq 2$ , select a series of adjacent lotteries (e.g., 8, 9, 10, and 11). Roughly 50%, 49%, and 54% of subjects in 2|RIVAL, 4|RIVAL, and 6|RIVAL select lotteries in this manner, respectably. Subjects also roughly evenly split their choices across riskier and safer lotteries relative to their stated favorite lottery. Subjects in 6|RIVAL on average pick 2.74 ( $\pm .59$ ) lotteries safer than their stated favorite lottery and 2.42 ( $\pm .57$ ) lotteries that are riskier than their favorite. Subjects in 4|RIVAL on average pick 1.42 ( $\pm .38$ ) lotteries safer than their favorite and 1.74 ( $\pm .41$ ) lotteries that are riskier than their favorite. Subjects in 2|RIVAL on average pick .86 ( $\pm .21$ ) lotteries that are safer than their favorite and .5 ( $\pm .19$ ) lotteries riskier than their favorite. While these results generally support Conjecture 1, the results are nonetheless incomplete as they fail to account for the distance between subjects' riskiest/safest lottery and their stated favorite.

We explore this in Table 6 which presents OLS estimates of the distance between subjects' riskiest/safest lottery from their stated favorite lottery (e.g., Safest Lottery Index Number - Favorite Lottery Index Number) as a function of assigned treatment, demographics and traits (Models 10 and 12). Models 9 and 10 estimate the difference between the safest lottery selected and favorite lottery. Models 11 and 12 estimate the difference between the favorite lottery and the riskiest. If subjects are treating outcomes as independent, we would expect to observe the constant term to be equal to zero; meaning subjects in the control select what they consider to be the best lottery. Additionally, we would expect the coefficient estimates on the all of the treatment dummies to not be significantly different from .5, 1.5, and 2.5 for 2|RIVAL, 4|RIVAL, and 6|RIVAL respectively. Results presented in Table 6 demonstrate mixed support of Conjecture 1. Relative to the stated favorite lottery, subjects pick a safest lottery that is statistically significantly safer than what is predicted by Conjecture 1. On the other hand, the distance between the stated best lottery and the riskiest lottery is often not statistically significantly different from the values predicted under Conjecture 1.

Taken together, our results suggest two primary findings: 1) subjects are not selecting lotteries that maximize expected utility and 2) subjects are treating the lotteries as independent but not perfectly so.

Table 6: Are Subjects Treating Outcomes as if they are Independent? Almost.

Dependent Variable	SAFEST - FAVORITE		FAVORITE - RISKIEST	
	Model 9	Model 10	Model 11	Model 12
2 RIVAL	2.587*** (0.598)	1.932*** (0.69)	0.799 (0.804)	0.757 (0.793)
4 RIVAL	3.84*** (0.966)	3.955*** (1.033)	3.067*** (0.819)	2.574*** (0.893)
6 RIVAL	4.933*** (0.735)	4.478*** (0.825)	3.346*** (0.826)	3.39*** (0.857)
CONSTANT	-0.723* (0.426)	0.415 (1.42)	0.723* (0.426)	1.025 (1.637)
CONTROLS	-	✓	-	✓
$R^2$	0.1831	0.2622	0.1073	0.1729
$H_0$ : 2 RIVAL = 0.5	0.0025	0.0397	0.7102	0.7461
$H_0$ : 4 RIVAL = 1.5	0.0165	0.0187	0.0572	0.2308
$H_0$ : 6 RIVAL = 2.5	0.0011	0.0177	0.3068	0.3001

**Notes:** Robust standard errors in parentheses. \*\*\*:  $p < .01$ , \*\*:  $p < .05$ , and \*:  $p < .10$ . All models are OLS estimating the difference between safest lottery a subject selected and their favorite or the difference between the their favorite lottery and the riskiest lottery selected.  $n = 177$ . Controls that are included in Models 10 and 12 are age, subjective risk preferences, education, income, and gender. Coefficient estimates of the controls are available upon request. Probability values derived from F-tests of equality of coefficients presented in the final 3 rows.

These findings are not well explained by other behavioral phenomenon. For example, risk aversion does not explain the observed pattern, as can be seen in Figure 2. The pattern is also not explained by reference dependent utility, as implausibly large penalty parameters are needed to do generate such safe choices. Finally, the pattern is not explained by max-min preferences, nor improved with experience. These alternatives are discussed in our previous working paper (Johnson and Webb, 2016).

## 7 Discussion

We have shown that when asked to select several lotteries from a fixed set of lotteries individuals select roughly equivalent portfolios regardless of whether the payoffs are rival or random. This is in stark contrast to the predicted behavior if individuals were expected utility maximizing. Yet, the observed choices in our experiment when payoffs are random are mostly in line with what one would predict under expected utility maximization. This suggests individuals are choosing their portfolios using independent probabilities despite the dependent nature of the outcomes when payoffs are rival. We consider this dependence neglect. These findings have implications for researchers who have modeled simultaneous search problems assuming expected value/utility maximization such as [Chade, Lewis, and Smith \(2013\)](#) and [Fu \(2014\)](#). In the context of college applications, the assumption of expected utility maximization would result in predicting too many applications sent to selective colleges as well as too few applications sent to less selective colleges, compared to dependence neglect predictions.

Our findings are consistent with the findings of [Pallais \(2015\)](#) which analyzes the effect of an exogenous increase in the number of ACT score reports a student can send to colleges after completing the ACT. She finds that “when students sent more score reports, they sent scores to a wider range of colleges: that is, those that were both more- and less-selective than any they would have sent scores to otherwise.” ([Pallais, 2015](#), p. 503) This behavior is inconsistent with expected utility maximization and, therefore, also with the no safety schools theorem of C&S. However, this type of behavior is predicted when individuals neglect dependence.

As a final note, our results have direct policy relevance and suggest that application subsidies for low-income students, such as those recently enacted by the College Board, will have relatively moderate success.<sup>17</sup> This is because, as our findings suggest, some of the additional applications sent would be sent to less selective schools, which will not increase the average quality of schools that low income students attend. As an alternative, our results suggest that the quality of schools attended by low-income students may be better improved by “expert advice” type interventions

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<sup>17</sup>Under these subsidies certain low income students are able to both write the SAT for free, and receive vouchers for up to four free college applications, at participating colleges. See <https://bigfuture.collegeboard.org/get-in/applying-101/college-application-fee-waivers> and <https://sat.collegeboard.org/register/sat-fee-waivers> for details.

(c.f., [Carrell and Sacerdote, 2013](#); [Hoxby and Avery, 2013](#); [Carrell and Sacerdote, 2017](#)) which encourage students to apply to more "stretch" schools. This policy prescription is consistent with recent empirical studies. For example, [Hoxby and Avery \(2013\)](#) finds that expert advice leads to students applying to more selective universities and therefore increases their likelihood of attending more selective schools. More research is needed to better understand why subjects make sub-optimal selections.

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## A Variable Descriptions

Below we present descriptions of the variables discussed in the text.

AGE is the subject's reported age.

MALE is a dummy variable that equals 1 if the subject indicates they are male; equal 0 otherwise.

INCOME is the subject's reported income (in US dollars). This variable is categorical, increasing in intervals of \$12,500 and can take a value from 1 to 10, with 1 indicating an income less than \$12,500 and 10 being greater than \$100,000.

EDUC is the subject's level of education. This variable is categorical, increasing in educational achievement.

RISK self reported risk preference. 0 if risk averse; 10 if full prepared to take risks.

AMB is a dummy variable equal to 1 if the subject was classified as ambiguity averse.

FAVORITE is the lottery that the subject specifies as the best.

LEAST FAV. is the lottery that the subject specifies as the worst.

RISKIEST is the subject's riskiest choice.

SAFEST is the subject's safest choice.

AVERAGE is the average index number of the lotteries in the subject's portfolio.

PICKED FAV. is a dummy variable equal to one if the subject picked what they thought of as the best lottery.

## B Possible Selection on Demographics

In Table B.1, we regress AGE, MALE, INCOME, EDUCATION, RISK, and AMB against the treatments to check for differences in subject characteristics across treatments. As expected, there are few substantive differences and demographic variables are roughly evenly distributed across treatment groups.

Table B.1: Distribution of Characteristics across Treatments

	AGE	MALE	INCOME	EDUC	RISK	AMB
TWO RI	-6.727 (4.211)	0.149 (0.103)	-0.258 (0.591)	0.344 (0.358)	0.986* (0.58)	0.098 (0.103)
TWO RA	-7.315* (4.349)	0.028 (0.106)	-0.708 (0.611)	-0.421 (0.37)	-0.095 (0.599)	0.088 (0.106)
FOUR RI	-7.946* (4.237)	0.234** (0.103)	-0.339 (0.599)	0.043 (0.36)	0.904 (0.587)	-0.077 (0.103)
FOUR RA	-8.762** (4.38)	0.121 (0.107)	-0.554 (0.615)	-0.492 (0.372)	-0.314 (0.603)	-0.084 (0.107)
SIX RI	-6.294 (4.237)	0.048 (0.103)	-0.53 (0.595)	0.787** (0.36)	0.562 (0.583)	-0.054 (0.103)
SIX RA	-8.741** (4.319)	0.14 (0.105)	-0.129 (0.607)	-0.003 (0.367)	0.513 (0.594)	0.325*** (0.105)
CONSTANT	41.341*** (2.929)	0.511*** (0.072)	4.554*** (0.411)	4.703*** (0.249)	4.788*** (0.403)	0.426*** (0.072)
Obs.	294	294	293	294	293	294
$R^2$	0.0211	0.0045	0.007	0.0535	0.0283	0.0695

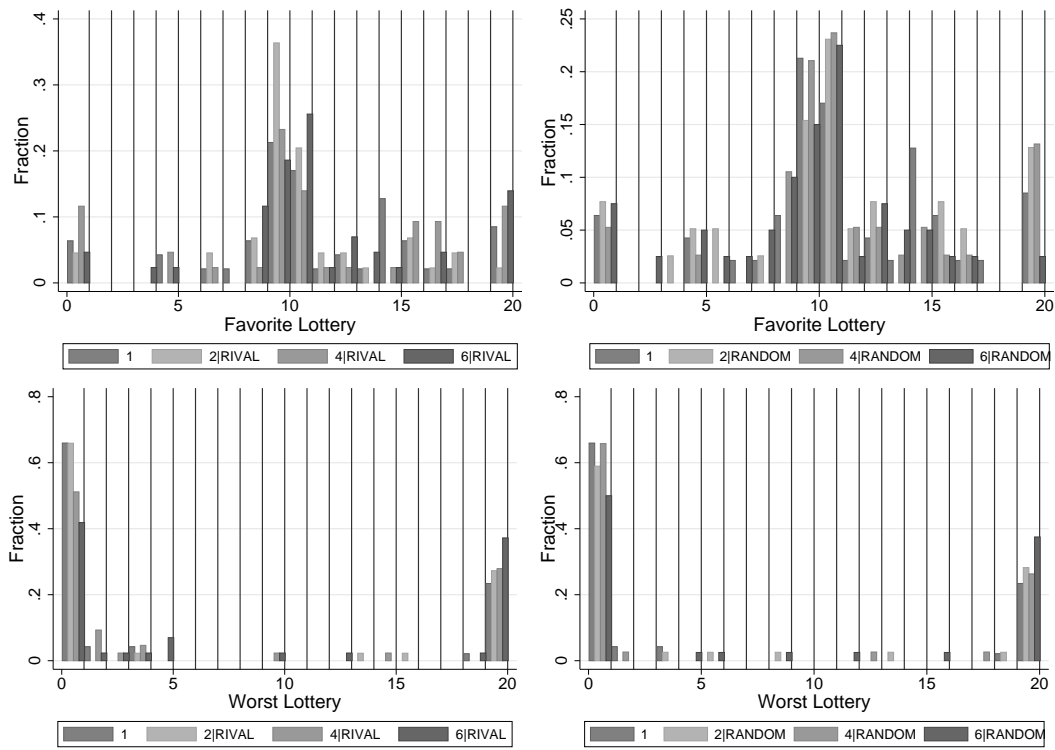
**Notes:** Standard errors in parentheses. \*\*\*:  $p < .01$ , \*\*:  $p < .05$ , and \*:  $p < .10$ . Treatment names abbreviated for space. RI - Rival, RA - Random. CONSTANT corresponds to the control (1).

## C Favorite and Least Favorite by Demographic Characteristics and Treatment

In regards to preferences over lotteries, subjects generally indicate that their favorite lottery,  $l^{1*}$ , is the safer lottery of the two that maximize the expected payoff — lottery 11. Subjects generally regard the riskiest (lottery 1) *or* the safest (lottery 20) lotteries as the worst. This is seen in Figure C.1 which presents the lotteries that subjects identify as their favorite and least favorite by treatment. It is important to note here that regardless of the number of choices subjects have or the way they are paid (i.e., RANDOM or RIVAL),  $l^{1*}$  should remain the same whether or not subjects have dependence neglect. At the same time, subjects should regard the worst lottery as the one furthest from  $l^{1*}$ . As  $l^{1*}$  is independent of the treatments, it also implies that the worst lottery should be as well - as logically it is the one furthest from  $l^{1*}$ . If subjects select the lottery that maximizes their expected value (e.g, lottery 10 or 11) as  $l^{1*}$ , it follows that the worst lottery is lottery 1 or 20 – which is what we observe.

In Table C.1, we estimate subjects’ ex-post classification of the best (FAVORITE) and worst (LEAST FAV.) lotteries as a function of the treatments and individual preferences using a Tobit specification. As one would expect, individual subjective risk preferences significantly influence subjects’ perceptions of the best lottery, but not of the worst lottery. Subjects who are relatively prepared to take risk tend to favor a lottery that is riskier than subjects who are less prepared to take risk. Additionally, there is little evidence that the treatment influenced subjects’ view of the lotteries. The lottery that subjects view as the best is invariant of the treatment. Similar results are found when examining what subjects regard as the worst lottery.

Figure C.1: FAVORITE and LEAST FAV. Lotteries by Treatment



**Note:** Top Panels are the Favorite Lottery, Bottom Panels are the Least Favorite Lottery.

Table C.1: Best and Worst Lottery by Treatment

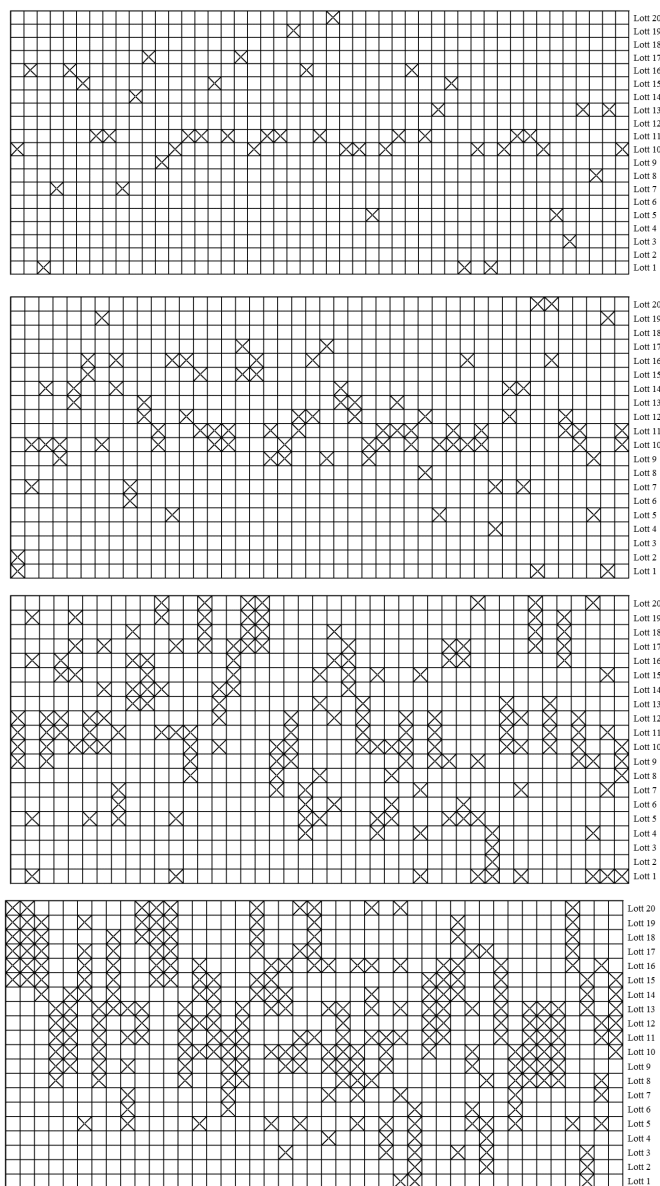
	FAVORITE		LEAST FAV.	
TWO RIVAL	-0.707 (1.145)	-0.521 (1.143)	3.234 (13.602)	3.061 (13.425)
TWO RANDOM	-0.285 (1.188)	-0.37 (1.18)	9.635 (13.86)	11.038 (13.692)
FOUR RIVAL	0.053 (1.159)	0.348 (1.162)	13.858 (13.427)	9.125 (13.316)
FOUR RANDOM	0.296 (1.196)	0.287 (1.189)	2.72 (14.135)	2.27 (13.972)
SIX RIVAL	0.255 (1.157)	0.427 (1.151)	26.691* (13.694)	24.983* (13.457)
SIX RANDOM	-1.797 (1.176)	-1.864 (1.187)	22.051 (13.896)	25.83* (14.052)
AMB	-	0.624 (0.658)	-	-13.596* (7.779)
RISK	-	-0.241** (0.117)	-	1.793 (1.363)
CONSTANT	11.73*** (0.799)	12.612*** (1.012)	-20.072* (10.299)	-22.864* (12.719)
Obs.	294	293	294	293
$R^2$	0.0027	0.0058	0.0088	0.0153
LL	20	20	168	168
UL	27	27	87	87

**Notes:** Tobit estimates. Standard errors in parentheses. \*\*\*:  $p < .01$ , \*\*:  $p < .05$ , and \*:  $p < .10$ . Upper Limit (UL) and Lower Limit (LL) are lotteries 1 and 20.

## D Portfolios Chosen by Subjects

In Figures D.1 and D.2, we present each subject's selected portfolio by treatment. Figure D.1 is made up of 4 sub-figures. Figure D.2 has 3 sub-figures. Each of the sub-figures in Figures D.1 and D.2 corresponds to a treatment: in Figure D.1 from top to bottom, 1, 2|RIVAL, 4|RIVAL, and 6|RIVAL; in Figure D.2 from top to bottom, 2|RAND, 4|RAND, and 6|RAND. Each column within a given sub-figure corresponds to a subject's choices in the experiment and rows correspond to the lotteries, with an "X" indicating that the subject chose a given lottery. Columns are sorted by subjects' subjective risk preferences - from risk averse (left) to completely willing to take risks (right). Lotteries are sorted by riskiness - from safe (top) to risky (bottom). Thus each column is the portfolio of lotteries selected by a subject. Subjects only participate once so each column reflects the choices of a specific subject.

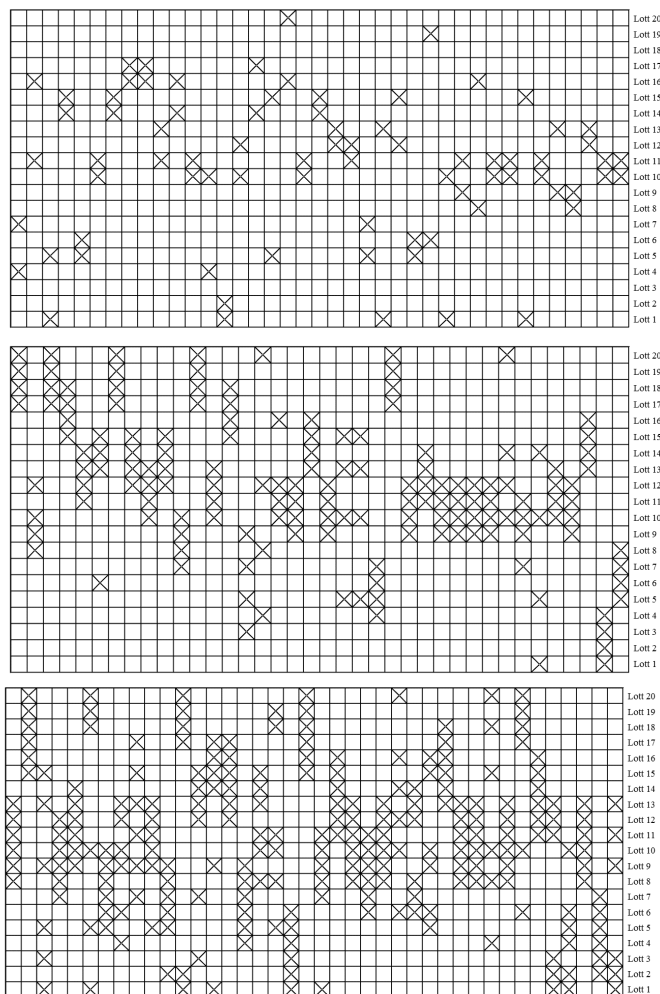
Figure D.1: Subjects' Decisions Sorted by Risk Preferences in RIVAL



**Notes:** The sub-figures indicate the portfolios chosen by subjects in the RIVAL treatments. From top to bottom, 1, 2|RIVAL, 4|RIVAL, and 6|RIVAL. Each column corresponds to a subject. “X” indicates a chosen lottery. Thus each column, within a given figure, is a subject’s portfolio.



Figure D.2: Subjects' Decisions Sorted by Risk Preferences in RANDOM



**Notes:** The sub-figures indicate the portfolios chosen by subjects in the RANDOM treatments. From top to bottom, 2|RAND, 4|RAND, and 6|RAND. Each column corresponds to a subject. “X” indicates a chosen lottery. Thus each column, within a given figure, is a subject’s portfolio.

## E Experiment Instructions

Below are the general instructions of the HIT. There are minor changes depending on the treatment, the exclusion of expected values, the ability to select the same lottery more than once, and experience. The specific instructions relating to the robustness checks and exploratory treatments are available upon request.

### Introduction

Welcome to the HIT! The instructions for this HIT are straightforward. If you follow them carefully, you can earn a considerable amount of money in addition to your participation fee of 25 cents. The additional amount you earn will be paid through the Amazon Mechanical Turk Bonus. Your confidentiality is assured.

In this HIT, there are 20 lotteries that vary both by their jackpots (payouts) and their odds (probability of winning). As such the expected value of the lotteries (probability of winning times the payout) also vary. You will be asked to select your **X** favorite lotteries, from the 20 available lotteries.

For each chosen lottery, a computer will randomly draw a number between zero and one to determine whether you have won that lottery. If the number drawn is less than or equal to the probability of the lottery winning, then you won that lottery.

For example, let us assume that lottery C has a probability of winning of 15 percent, then any number drawn by the computer between 0.00 and 0.15 would win the lottery and any number between 0.16 and 1.00 would not win the lottery. Your payment for this HIT will be the maximum payment from any successful lottery. If you were to win only one lottery, then the payout from that lottery would be your payment. If you were to win two lotteries, your payment would be the highest value of the two payouts. If you do not win any lotteries, you will only receive your participation fee.

Before you begin, we would like you to complete a brief survey to make sure that you comprehend written English.

Do not click the Submit button until specifically instructed to do so.

### Survey

Before we begin please take a few minutes to complete this short survey. When you are finished, please click the “next” button. Note there are two English comprehension questions. If you fail to answer any of them correctly, you will be asked to return the HIT and will not be able to continue. After you finish selecting your favorite lotteries, you will be instructed to complete another short survey.

1. What is your gender?
2. What is your age?

3. What country do you currently live in?
4. Paul bought a baseball for **X** dollars. Jim bought a candybar for one dollar. How much did Paul's baseball cost?
5. You and your friend are playing a game with a coin. If the coin is flipped and ends up heads you win a dollar. If it ends up tails you win nothing. What is the expected value of this game (in CENTS)?
6. What is the expected value of a game that pays 200 dollars with probability 25 percent? Please just enter as an integer number.

Do not click the Submit button until specifically instructed to do so.

### Practice

Practice: for example, you are asked to select your favourite 3 lotteries from lotteries A, B, C, D and E. The lotteries' payoffs are as follows:

	Lottery A	Lottery B	Lottery C	Lottery D	Lottery E
Prob	10 %	20%	50%	60%	80%
Prize	\$4.50	\$4.00	\$3.00	\$2.00	\$1.00
EV	\$0.45	\$0.80	\$1.50	\$1.20	\$0.80

From the table above you can see that Lottery A pays 4.50 with a probability of 10%, Lottery B pays 4.00 with a probability of 20%, Lottery C pays 3.00 with a probability of 50%, Lottery D pays 2.00 with a probability of 60% and Lottery E pays 1.00 with a probability of 80%.

You select lotteries A, C, and E. The outcomes of each of these lotteries are as follows:

1. Lottery A draws the number .2, which is greater than .1 and therefore unfavorable to you.
2. Lottery C draws the number .1, which is less than .5 and therefore favorable to you.
3. Lottery E draws the number .8, which is equal to .8 and therefore favorable to you.

Your earnings for the lottery part of the HIT would therefore be 3.00 dollars. This is because the outcome of lottery A was unfavorable to you. While both lotteries C and E were favorable to you, the favorable outcome of Lottery C (\$3.00) is greater than the favorable outcome of Lottery E (\$1.00).

	Lottery A	Lottery B	Lottery C	Lottery D	Lottery E
Prob	10 %	20%	50%	60%	80%
Prize	\$4.50	\$4.00	\$3.00	\$2.00	\$1.00
EV	\$0.45	\$0.80	\$1.50	\$1.20	\$0.80

When you are asked to make your actual decisions, you will see a chart like the one shown on the practice stage but there will be more lotteries and there will be a box underneath each lottery. In each of these boxes, there will be two radio buttons. One radio button will correspond to “No” while the other will correspond to “Yes”. The “No” button will be indicated with a “N” while the “Yes” button will be indicated with a “Y”. You will use these radio buttons to indicate your preferred lotteries. If a given lottery is among your **X** preferred lotteries, click the corresponding “Yes” radio button. If not, click the “No” radio button.

After you have indicated your **X** preferred lotteries, you will be asked to click the “next” button to complete the final parts of the HIT.

Do not click the Submit button until specifically instructed to do so.

## Game

Please indicate your **X** favorite lotteries. After you have indicated your **X** preferred lotteries, click the “next” button to finish up the final parts of the HIT.

Do not click the Submit button until specifically instructed to do so.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
Prob	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%	55%	60%	65%	70%	75%	80%	85%	90%	95%	100%
Prize	\$5.00	\$4.75	\$4.50	\$4.25	\$4.00	\$3.75	\$3.50	\$3.25	\$3.00	\$2.75	\$2.50	\$2.25	\$2.00	\$1.75	\$1.50	\$1.25	\$1.00	\$0.75	\$0.50	\$0.25
EV	\$0.25	\$0.48	\$0.68	\$0.85	\$1.00	\$1.13	\$1.23	\$1.30	\$1.35	\$1.38	\$1.38	\$1.35	\$1.30	\$1.23	\$1.13	\$1.00	\$0.85	\$0.68	\$0.48	\$0.25
Pick																				

## Game Continued

You have now indicated your most preferred lotteries. We would now like to find out what you think are the best and worst lotteries. Below we have presented a table just like you saw on the previous screen and have indicated the lotteries you selected with the word “Picked”. That is, if you selected Lottery A than you would see the word “Picked” located in the cell above it.

Using the radio buttons in the row marked “Best” below, please indicate the lottery you think is the best of all the lotteries by clicking on the radio button underneath your favorite lottery. After you have selected the lottery that you think is the best, use the radio buttons in the “Worst” row to indicate the lottery that you think is the worst of all the lotteries.

Once you have finished selecting what you think are the best and worst lotteries, click the “next” button to go to the final part of the HIT. You will make an additional 10 cents for completing this final portion of the HIT.

Reminder! Do not click the Submit button until specifically instructed to do so.

## **END**

Thank you for your participation! Please answer the questions below. If you do so, you will earn an additional 10 cent bonus! If you do not wish to complete the survey. Feel free to submit the HIT!

**DIRECTIONS:** People differ in the ways they act and think in different situations. This is a test to measure some of the ways in which you act and think. Read each statement and click on the appropriate circle on the right side of this page. Do not spend too much time on any statement. Answer quickly and honestly. [Answered from a four point scale ranging from Rarely/Never - Almost Always/Always]

I plan tasks carefully.

I do things without thinking.

I make up my mind quickly

I am happy-go-lucky.

I don't pay attention.

I have racing thoughts.

I plan trips well ahead of time.

I am self controlled.

I concentrate easily.

I save regularly.

I squirm at plays or lectures.

I am a careful thinker.

I plan for job security.

I say things without thinking.

I like to think about complex problems.

I change jobs.

I act on impulse.

I get easily bored when solving thought problems.

I act on the spur of the moment.

I am a steady thinker.

I change residences.

I buy things on impulse.

I can only think about one thing at a time.

I change hobbies.

I spend or charge more than I earn.

I often have extraneous thoughts when thinking.

I am more interested in the present than the future.

I am restless at the theater or lectures.

I like puzzles.

I am future oriented.

1. What is your Nationality?
2. Which of the following best describes your highest achieved education level?
3. What is the total income of your household?
4. Why do you complete tasks in Mechanical Turk? Please check any of the following that applies:

Fruitful way to spend free time and get some cash.

For primary income purposes (e.g. gas, bills, groceries, credit cards).

For secondary: income purposes, pocket change (for hobbies, gadgets, going out).

To kill time.

I find the tasks to be fun.

I am currently unemployed, or have only a part time job.

5. How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? [Answered using a 0 to 10 point scale where 0 corresponds to Risk Averse and 10 corresponds to Fully Prepared to take risks]
6. People can behave differently in different situations. How would you rate your willingness to take risks in the following areas? [Answered using a 0 to 10 point scale where 0 corresponds to I avoid risk and 10 corresponds to Fully Prepared to take risks]

while driving?

in financial matters?

during leisure and sport?

in your occupation

with your health?

your faith in other people?

7. Please consider what you would do in the following situation: Imagine that you had won 100,000 dollars in the lottery. Almost immediately after you collect the winnings, you receive the following financial offer from a reputable bank, the conditions of which are as follows: There is the chance to double the money within two years. It is equally possible that you could lose half of the amount invested. You have the opportunity to invest the full amount, part of the amount or reject the offer.

What share of your lottery winnings would you be prepared to invest in this financially risky, yet lucrative investment?

8. Suppose there is a bag containing 90 balls. You know that 30 are red and the other 60 are a mix of black and yellow in unknown proportion. One ball is to be drawn from the bag at random. You are offered a choice to (a) win \$100 if the ball is red and nothing if otherwise, or (b) win \$100 if it's black and nothing if otherwise. Which do you prefer?
9. The bag is refilled as before, and a second ball is to be drawn from the bag at random. You are offered a choice to (c) win \$100 if the ball is red or yellow, or (d) win \$100 if the ball is black or yellow. Which do you prefer?

Please submit the HIT when you are done.

# F Screen Shot of Decision Stage

Figure D.3: Screen Where Subjects are Asked To Choose From Menu of Lotteries

Secure | https://workspaces.mturk.com/mturk/accept?hitId=3CPLMF3EUSAYZCFAD77WUOT1MCNLV8&prevHitSubmitted=false&prevRequester=David+Johnson&requesterId=A15ZDWN6Q4OQ&previewReward=USD0.25&hitAutoAppDelayInSeconds=259200&grou...

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Your Account | **HITS** | Qualifications | 77,630 HITS available now

David Johnson | Account Settings | Sign Out | Help

All HITS | HITS Available To You | HITS Assigned To You

Find HITS containing  that pay at least \$ 0.00  for which you are qualified require Master Qualification

Timer: 00:02:18 of 60 minutes

Finished with this HIT?  Let someone else do it?  ☐ Automatically accept the next HIT

Total Earned: \$1.69  
Total HITS Submitted: 44

Pick some lotteries! (Win a bonus!)  
Requester: David Johnson  
Qualifications Required: None

Reward: \$0.25 per HIT | HITS Available: 1 | Duration: 60 minutes

Please indicate your 6 favorite lotteries. After you have indicated your 6 preferred lotteries, click the "next" button to finish up the final part of the HIT.

Do not click the Submit button until specifically instructed to do so.

	Lottery A	Lottery B	Lottery C	Lottery D	Lottery E	Lottery F	Lottery G	Lottery H	Lottery I	Lottery J	Lottery K	Lottery L	Lottery M	Lottery N	Lottery O	Lottery P	Lottery Q	Lottery R	Lottery S
Probability of Winning	2%	10%	10%	20%	25%	30%	30%	40%	40%	50%	50%	60%	60%	70%	70%	80%	80%	90%	90%
Expected Value	\$1.00	\$4.75	\$4.00	\$4.25	\$4.00	\$1.75	\$0.00	\$0.25	\$0.00	\$1.75	\$1.00	\$0.25	\$0.00	\$1.75	\$1.00	\$1.25	\$1.00	\$0.75	\$0.50
Expected Value	\$0.25	\$0.45	\$0.80	\$0.25	\$1.00	\$1.25	\$0.25	\$0.30	\$0.25	\$1.25	\$1.25	\$0.25	\$0.25	\$1.25	\$1.25	\$1.00	\$0.25	\$0.45	\$0.25
Decision	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N	<input type="radio"/> Y <input type="radio"/> N

Finished with this HIT?  Let someone else do it?  ☐ Automatically accept the next HIT

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